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ROBUST ENERGY FEATURES DETECTION TECHNIQUE BASED ON WAVELET FOR GLAUCOMATOUS IMAGE CLASSIFICATION

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Abstract: **Glaucoma is the eye disease can lead to the blindness. It is often associated with the increase the pressure (IOP) of the fluid in the eye, and it is called "Silent Thief of Sight". In worldwide Glaucoma is the leading cause of blindness, the detection of glaucoma is very expensive. This method to detect glaucoma using fundus images. In image processing techniques, such as preprocessing, wavelet features extraction are used for the detection of the many features. We have extracted features such as Average, Energy, Contrast, Moments, using wavelet feature extraction method. These features are automatically classified the normal and glaucoma images using Support vector machine(SVM) classifier. The images were collected from the Kasturba Medical College. In this study, for each subject, 20 images were analyzed. By extracting information of pixel average value from the images, it is possible to obtain the necessary value for classification.**
Keywords: **Wavelet, SVM, Glaucoma.**

I. INTRODUCTION

Glaucoma is one of the most common causes of blindness. It is induced by the progressive loss of retinal nerve fibers in the par papillary region. Lost fibers cannot be revitalized but the progression of the disease can be stopped [1]. For this reason, early detection of glaucoma is essential for affected patients. Diagnosis is commonly done by direct examination of the important neuro retinal rim [2] using an ophthalmoscope or based on digital retina images acquired by de-vices such as the Heidelberg Retina Tomography (HRT) [3] or the Kowa Non.

Myd fundus camera (Fig. 1). In this work, we use the modality of color fundus photographs. The acquisition is suitable for screening applications because fundus photos can be taken very fast and without any inconvenience for patients. Existing computer aided analysis of retina images are based on segmentation which is mostly done manually or by semi-automated methods [4]. Different research groups investigate in the field of getting and selecting segmentation measurements from HRT images [5, 6]. Segmentation based techniques have one major drawback: small errors in segmentation may lead to significant change in the measurements and thus the estimation and diagnosis. In our approach, the feature extraction and classification is fully automated and is not segmentation dependent. This appearance based approach is well-known from object and face recognition [7, 8]. It is a data driven technique based on statistical evaluation of the image data, e.g. by Principal Component Analysis (PCA). This promising approach is new in the field of retina imaging. To provide a good basis for further investigations, we analyze the effect of normalizing the images by preprocessing methods on classification results. We show that reducing disease independent variations is possible without removing information that discriminates between healthy and glaucomatous eyes. On one hand, non-uniform illumination is a general problem in retinal imaging. It is due to the small size of the objects and the complexity of the optic system (including both the camera and the eye) involved in the imaging process. Such in homogeneities have to be corrected. On the other hand, blood vessels in retina images seem to be a distracting feature when diagnosing glaucoma.

Database

The retinal images were collected from the Kasturba Medical College, Manipal, India (http://www.manipal.edu). The doctors in the ophthalmology department of the hospital manually curate the images based on the quality and usability of samples. The ethics committee approved the use of the images for this project. the images were taken with a size of 560 × 720 pixels and stored in lossless JPEG format . The dataset contains40 fundus images: 20 normal and 20 open angle glaucomatous images from 20 to 70 year-old persons. The camera, microscope, and a light source were used to acquire the retinal images to diagnose diseases. Fig. 1(i) and (ii) presents typical normal image and glaucoma image

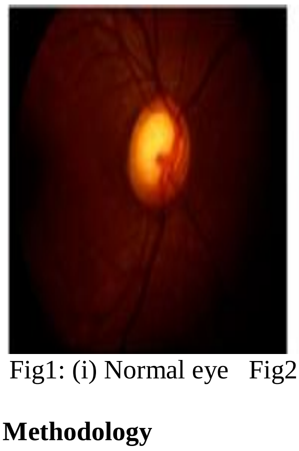


Fig1: (i) Normal eye Fig2 (ii)Glaucoma eye

Methodology

The images in the dataset were subjected to standard histogram equalization. The objective of applying histogram equalization was twofold: to assign the intensity values of pixels in the input image, such that the output image contained a uniform distribution of intensities, and to increase histogram dynamic range. The following detailed procedure was then employed as the feature extraction and classification

Image Decomposition

Application of wavelet transform in image processing is one of the active areas in wavelet studies. 2d wavelet transform can be considered as an extent of one dimensional wavelet transform. . It is used to solve the problem like system modeling used in control systems and construction of autoregressive models. For 2D wavelet transform, we consider separable wavelet basis to decompose the image as follows a separable wavelet basis of $L^2(R^2)$ space is constructed using tensor product of a scaling function φ and a wavelet function ψ. Consider φ, ψ and $\tilde{\varphi}$ and $\tilde{\psi}$ as two dual pairs of scaling and wavelet functions in a biorthogonal wavelet transform in $L^2(R)$. Accordingly, three wavelet functions can be defined for the decomposition stage as the product of scaling and wavelet functions φ, ψ as follows:

$$\psi^0(x,y)=\varphi(x)\varphi(y),$$
$$\psi^2(x,y)=\psi(x)\varphi(y)$$
$$\psi^1(x,y)=\varphi(x)\psi(y)$$
$$\psi^3(x,y)=\psi(x)\psi(y)$$

We have three orientations for details:

- horizontal,
- vertical and
- diagonal

Note, to cover the entire image using one dimensional wavelets, image consist of rows or columns which are one dimensional in rows or columns. We apply wavelet transform for each row (i.e. keeping x constant but changing y) starting from the top row. Then apply wavelet transform on the results of row operations but now move column-wise starting from the left column where we use wavelet or scaling function depending on whether we want A1, DH1, and DV1 or DD1 signal components. Since we are using one dimensional wavelet transform at each scan of x or y direction.

Feature extraction

Two dimensional dwt used to extract the energy features from images. The DWT is employed to various filters like biorthogonal (bio3.3, bio3.5, bio3.7), daubechies (db3), and symlets (sym3) .to use this filters we have to find the coefficient of wavelet. Since the number of features in these

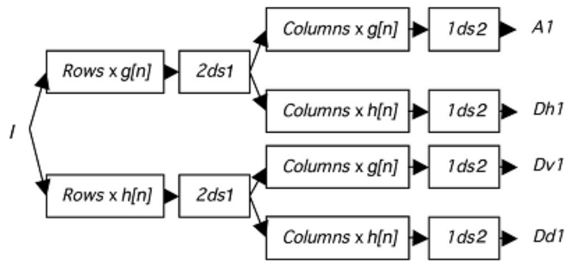

Fig 2:2-D-DWT decomposition

matrices is increase, and since we only need a single number as a represent feature, we employ averaging methods to determine such single valued features. The definitions of the three features that were determined using the DWT coefficients are in order. Equations (1) and (2) determine the averages of the corresponding intensity values, whereas (3) is an averaging of the energy of the intensity values

$$Average\ Dh1 = \frac{1}{p \times q} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dh1(x,y)| \quad (1)$$

$$Average\ Dv1 = \frac{1}{p \times q} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dv1(x,y)| \quad (2)$$

$$Energy = \frac{1}{p^2 \times q^2} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dv1(x,y)^2| \quad (3)$$

Classification

The aim of Support Vector classification is to devise a computationally efficient way of learning 'good' separating hyper planes in a high dimensional feature space, where by 'good' hyperplanes we will understand ones optimizing the generalization bounds , and by 'computationally efficient' mean algorithms able to deal with sample sizes of the order of 100 000 instances. The generalization theory gives clear guidance about how to control capacity and hence prevent over fitting by controlling the hyperplane margin measures, while optimization theory provides the mathematical techniques necessary to find hyperplanes optimizing these measures. Different generalization bounds exist, motivating different algorithms: one can for example optimize the maximal margin, the margin distribution, the number of support vectors, etc. For instance-label pair (x_i, y_i) with $x_i \in \mathbb{R}^n$, $y_i \in \{-1,1\}$ for $1 \le i \le n$ where n is the number of instances, the following optimization problem needs to be solved for SVMs.

In the above equation, w is decision hyperplane normal vector, C is the penalty parameter for error term and □ maps a training instance x_i to higher dimensional space.

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i$$

subject to

$$y_i \left(w^T \phi(x_i) + b0 \geq 1 - \xi_i, \xi_i \geq 0 \right. \quad \text{--(4)}$$

The kernel K is defined as:

K □x_i , x_j □□□□□x_i □^{T} □□x_j□□□□□□

Software Requirement and description

We have used windows XP is the operating system and tool is Matlab R 2009a. MATLAB is a high-performance language .t he *MATLAB* environment offers a variety of data plotting functions plus a set of GUI tools to create, and modify *graphic* displays.

II. RESULTS AND DISCUSSIONS

The code was developed by using mat lab and the result is examined It classify the data's into glaucomatous and normal images. Support vector machine is used for classification, learning of supervision is achieved by classification Feature extraction is done by using wavelet energy feature extraction method, and after feature extraction testing and classification rate is done. The performance of SVM classifier is shown in fig3.

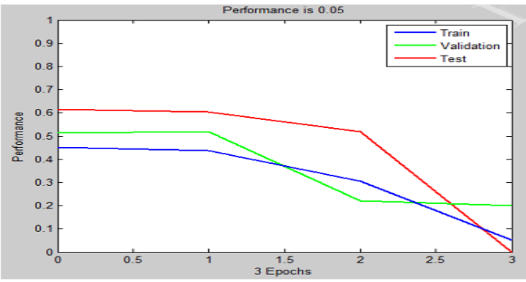

Fig 3: Performance graph for SVM

III. CONCLUSION

This method demonstrates the feature extraction process using three wavelet filters. The daubechies, symlets and bi-orthogonal are the wavelet filters used. The wavelet coefficients obtained are then subjected to average and energy calculation resulting in feature extraction. The classification is done using SVM which provides higher accuracy. We can conclude that the energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy.

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